# Optimization Challenges in Energy Systems

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Argonne NATIONAL LABORATORY

# Outline

## Challenges in Optimization from Energy Perspective

1. **Motivation**
   - **Next-Generation Power Grid**
   - **Decision-Making Hierarchy**
   - **Who? Domains? Frequency?**

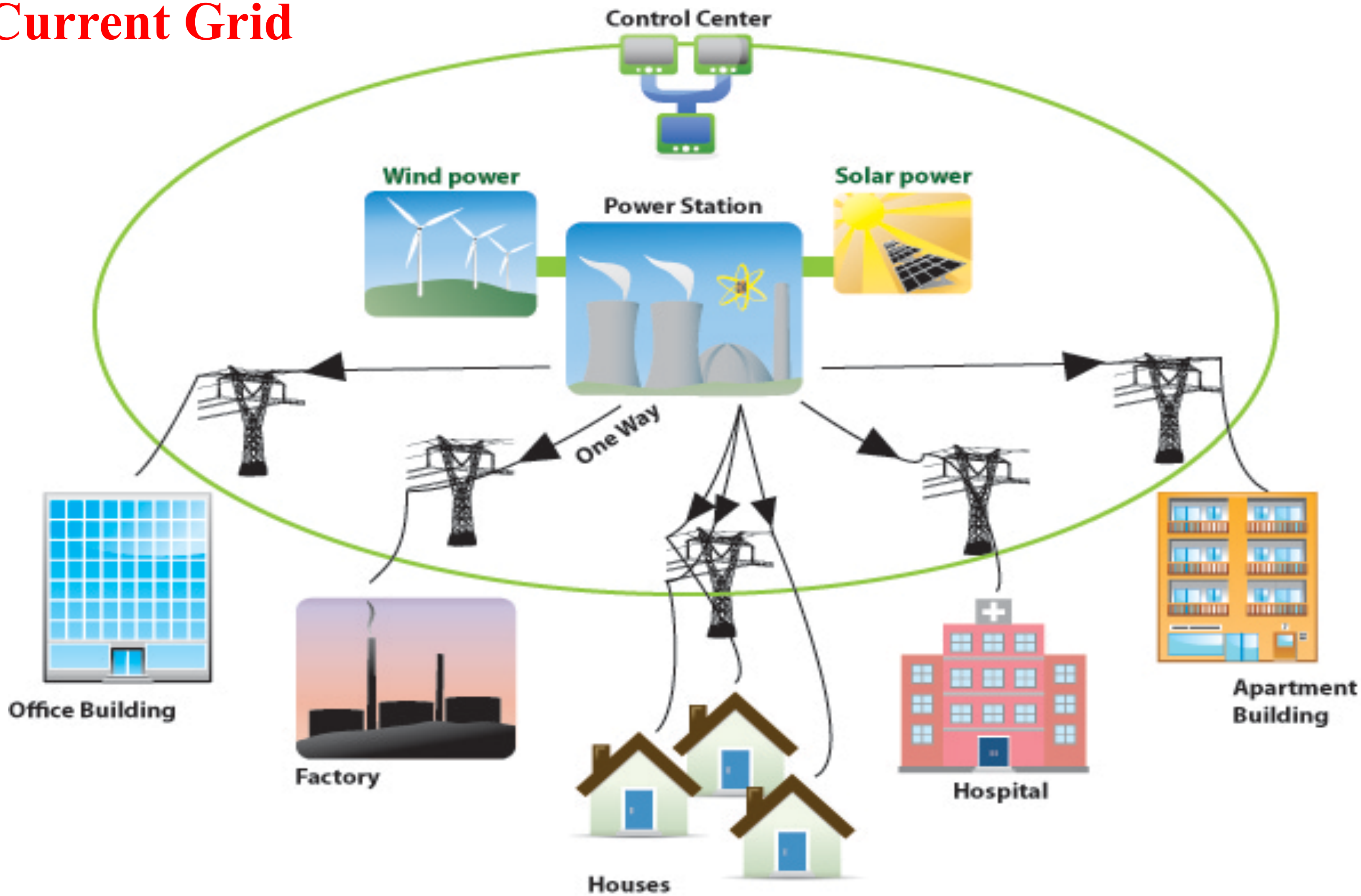
2. **Optimization Issues**
   - **Models and Complexity – LP/QP, NLP, MPEC, MI(N)LP**
   - **Uncertainty Quantification - Data Assimilation and Machine Learning**
   - **Dynamics and Decentralization -Gaming-**

3. **Conclusions**

# 1. Motivation

# Motivation

## Current Grid



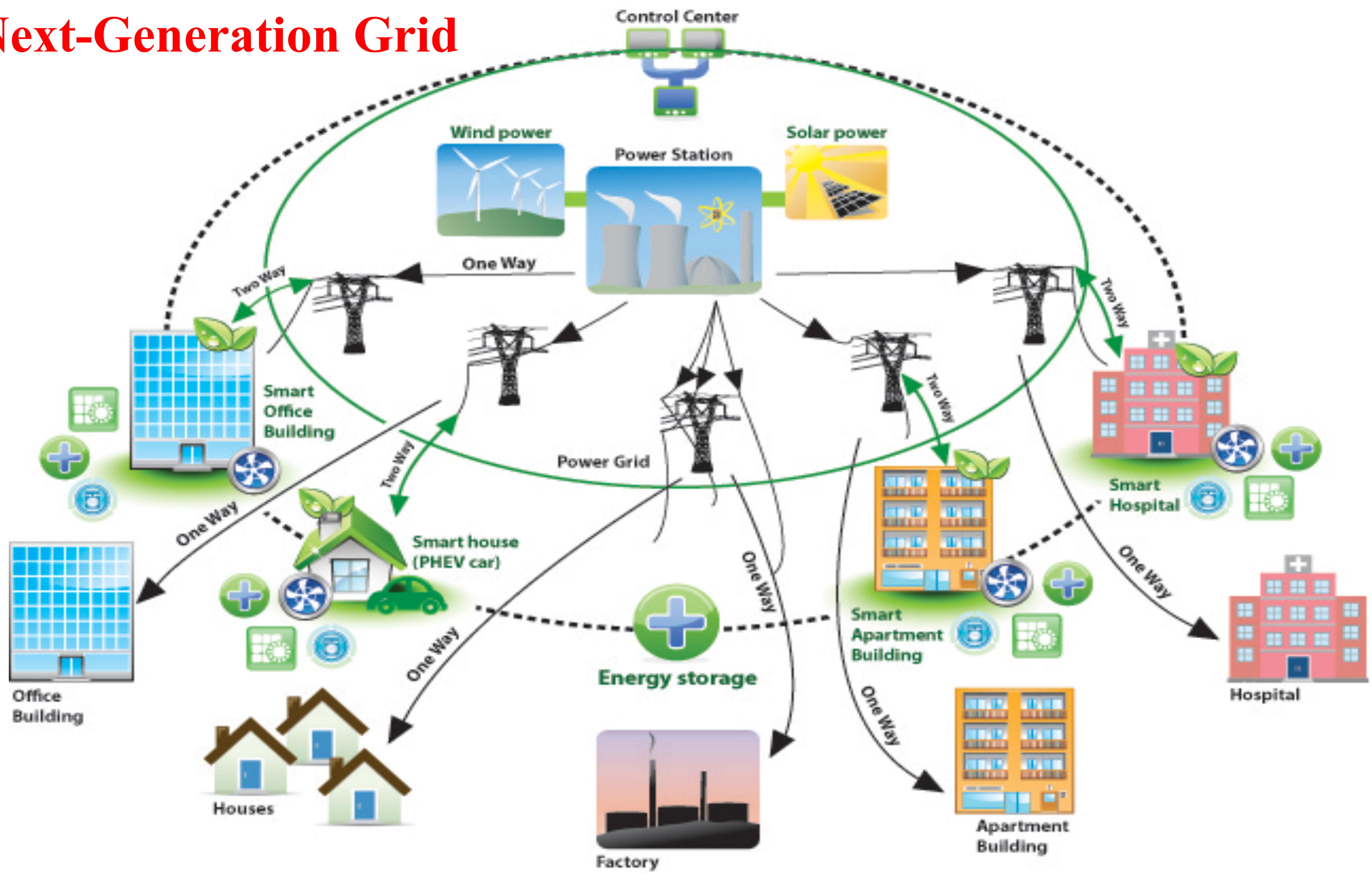

~ 70% Electricity from Coal – $CO_2$ Emissions

Limited Market Control – Demands are Inelastic, No Storage

~ 20% Energy Losses - Transmission, Demand Shedding, and Wind Curtailment

# Motivation

## Next-Generation Grid




Major Adoption of <u>Renewables</u> -30%-

<u>Elastic</u> Demands, Distributed Generation and Storage, Real-Time Pricing

All Players use Optimization – How to Coordinate Time-Scales?

# Motivation

**Decision Making Structure and Optimization Tasks**

**Planning**

**Transmission/Generation Expansion:** ISO, Yearly, MILP

**Markets**

**Unit Commitment:** ISO, Daily, DC Flow, MILP

**Day-Ahead Bidding:** GENCOs/Utilities, Daily, LP/QP

**Economic Dispatch:** ISO, 5 Minutes, DC Flow, LP/QP

**Real-Time Bidding:** GENCOs/Utilities, 5 Minutes, LP/QP

**Control**

**AC Power Flow:** ISO, 1-2 Minutes, NLP

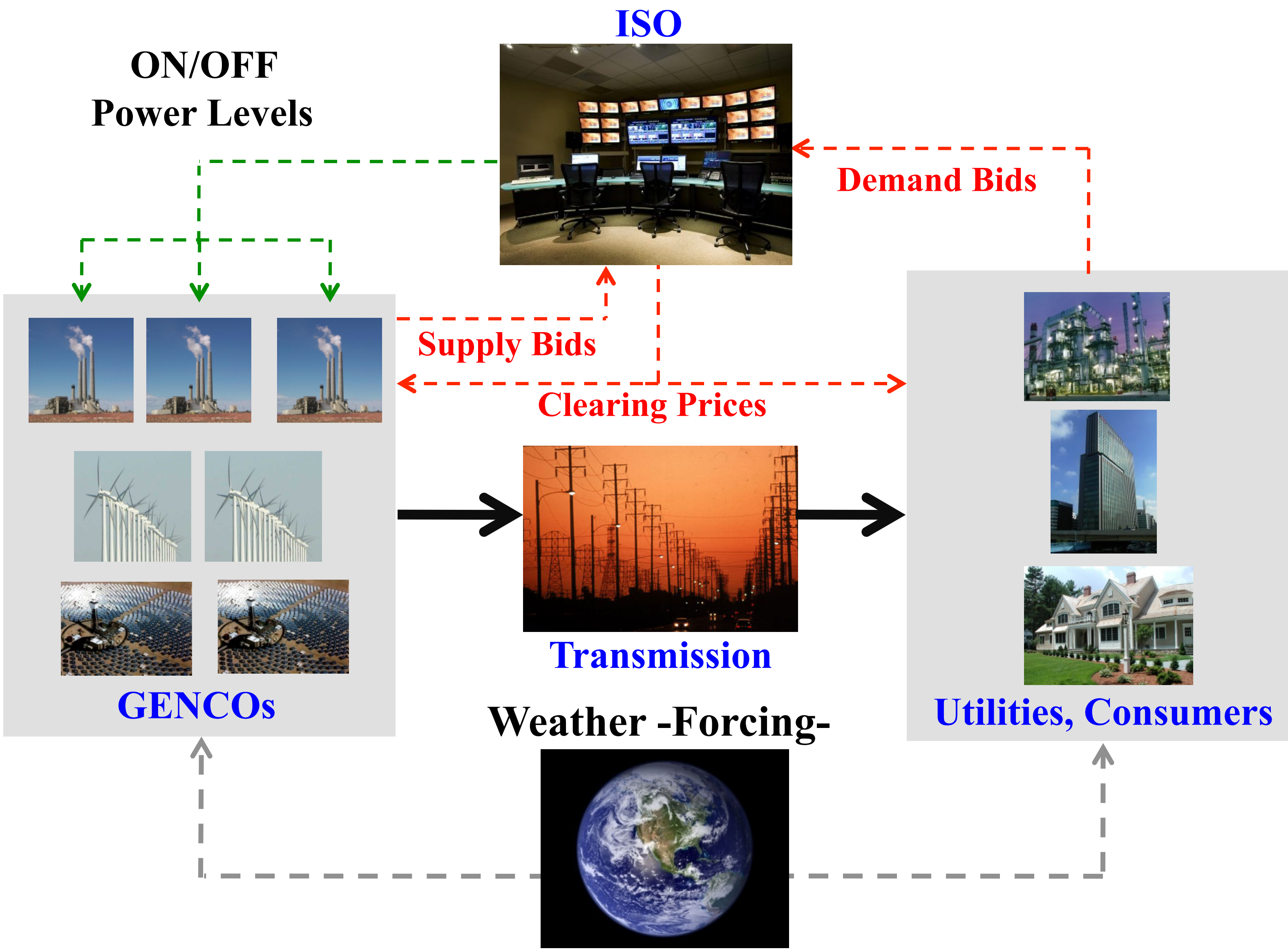
**State Estimation:** ISO, 1-2 Minutes, QP/NLP

**Generation Control:** GENCOs, Seconds, QP/NLP

**Voltage and Dynamic Stability:** ISO, MilliSeconds, No Optimization

**Energy Management:** Utilities/Consumers, Seconds/Minutes, LP/QP/NLP

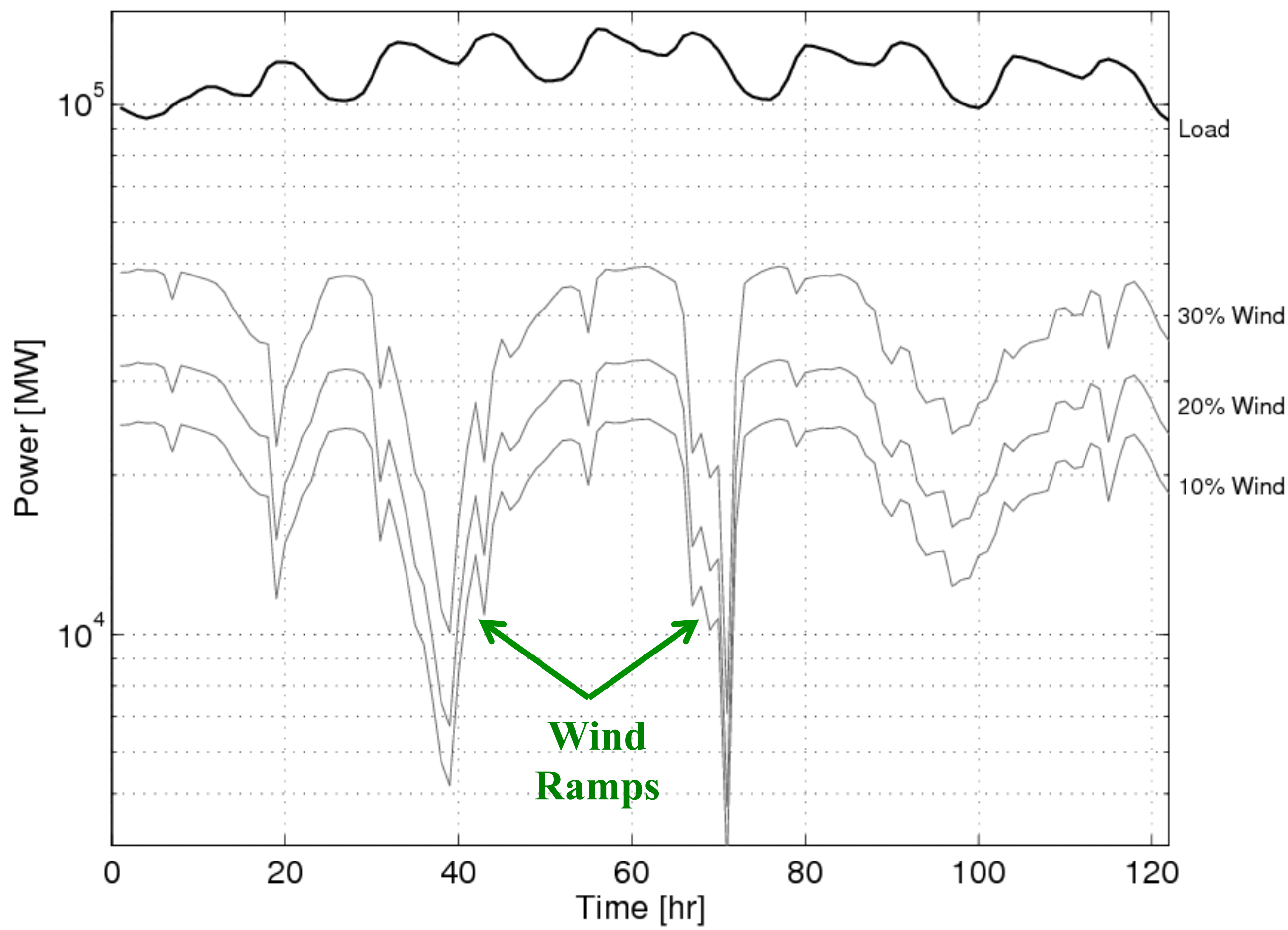
# Motivation




**Dynamic & Uncertain Forcing Factors -Weather- Drive Markets**

# Motivation

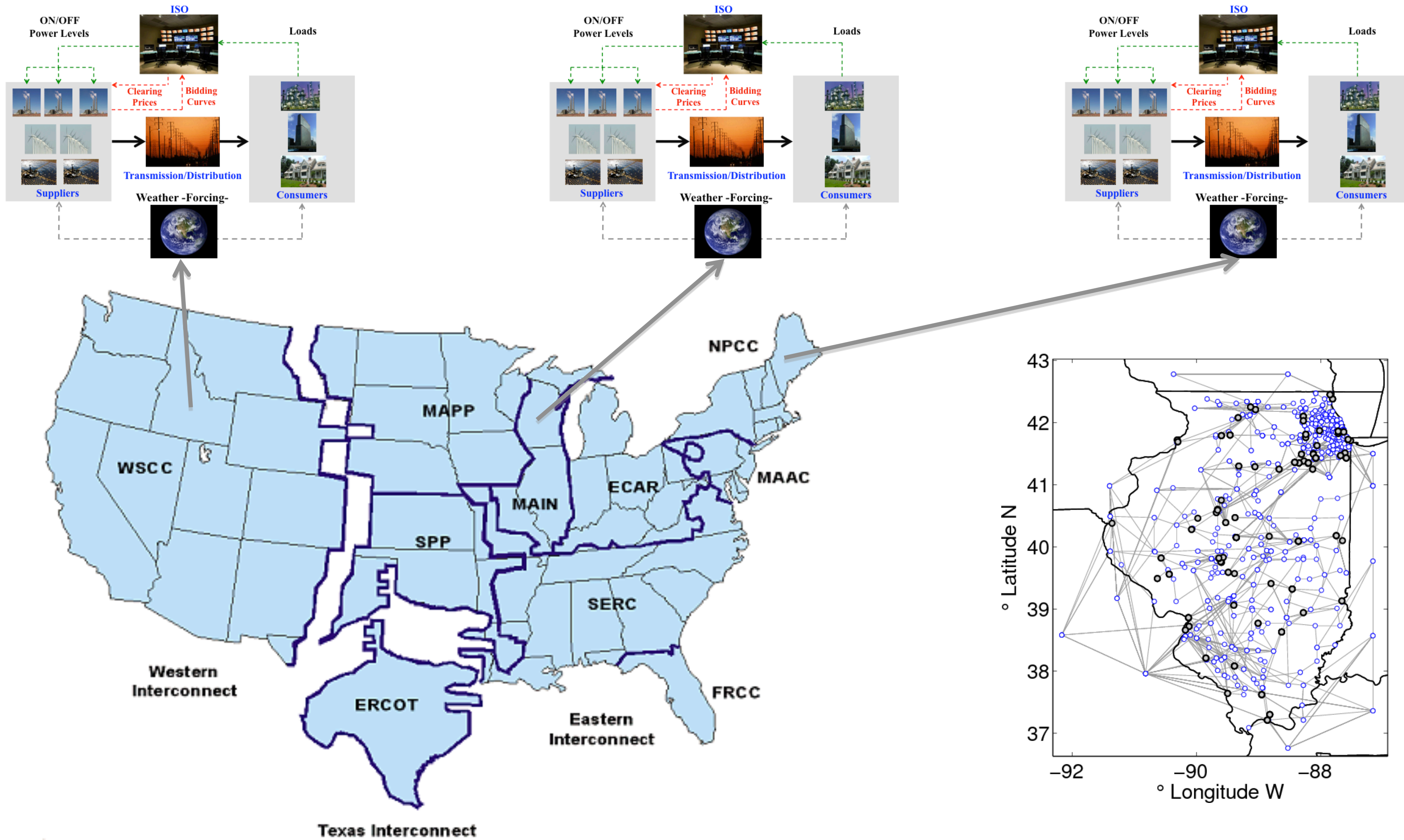
**Supply (Wind) and Elastic Demands Vary at <u>Higher Frequencies</u>**




**<u>Anticipating</u> Forcing Factors is Critical -Minimize Reserves-**

**Longer <u>Foresight</u> Horizons and Faster <u>Updates</u> Needed**

# Motivation




**Interconnect Level Transactions - Key for High Efficiency and Lower Prices**

**- Hydro, Wind, Geothermal, Solar, Eastern Demands**

**Transmission Network Expansion - Need Infrastructure to Enable Exchanges**

# 2. Optimization Issues

# A Canonical Model

**Transmission/Generation Expansion**

**Horizons of 10 to 20yr – MILP with $O(10^4)$ Integers & $O(10^8)$ Continuous – Memory Constraints**

**Day-Ahead and Real-Time Market Clearing**

**Horizons of 1 to 36hr – MILP with $O(10^3)$ Integers & $O(10^6)$ Continuous – Time Constraints**

$$\min \sum_{k\in\mathcal{T}}\sum_{j\in\mathcal{G}} c_j \cdot G_{k,j} \cdot \mathbf{y}^G_{k,j} + c_j^{\uparrow} \cdot (\mathbf{y}^G_{k+1,j} - \mathbf{y}^G_{k,j}) + c_j^{\downarrow} \cdot (\mathbf{y}^G_{k,j} - \mathbf{y}^G_{k+1,j}) + \sum_{j\in\mathcal{L}} c_j^L \cdot (\mathbf{y}^L_{k+1,j} - \mathbf{y}^L_{k,j})$$

**Cost Function**

$$\text{s.t. } G_{k+1,j} = G_{k,j} + \Delta G_{k,j},\ k\in\mathcal{T}, j\in\mathcal{G}$$

**Dynamics -Ramps-**

$$\sum_{(i,j)\in\mathcal{L}_j} P_{k,i,j} + \sum_{i\in\mathcal{G}_j} G_{k,i} = \sum_{i\in\mathcal{D}_j} D_{k,i},\ k\in\mathcal{T}, j\in\mathcal{B}$$

$$|P_{k,i,j} - b_{i,j}(\theta_{k,i} - \theta_{k,j})| \le \mathrm{M}_{i,j} \cdot \mathbf{y}^L_{k,i,j}, k\in\mathcal{T}, (i,j)\in\mathcal{L}$$

**Network**

$$0 \le G_{k,j} \le G_j^{max} \cdot \mathbf{y}^G_{k,j},\ k\in\mathcal{T}, j\in\mathcal{G}$$

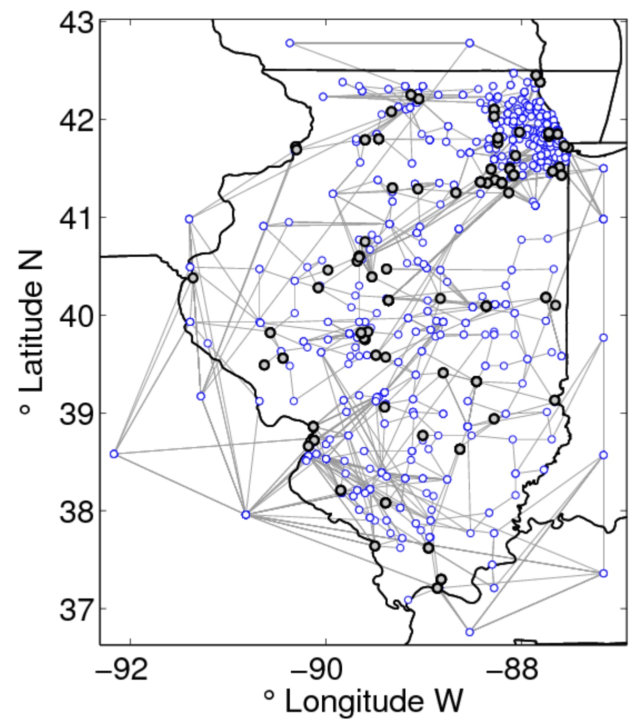
$$|\Delta G_{k,j}| \le \Delta G_j^{max} \cdot y^G_{k,j},\ k\in\mathcal{T}, j\in\mathcal{G}$$

$$|P_{k,i,j}| \le P_{i,j}^{max} \cdot \mathbf{y}^L_{k,i,j},\ k\in\mathcal{T}, (i,j)\in\mathcal{L}$$

$$|\theta_{k,j}| \le \theta_j^{max},\ k\in\mathcal{T}, j\in\mathcal{B}$$

$$\sum_{\ell=k}^{k+UT-1} \mathbf{y}^G_{\ell,j} \ge UT\left(\mathbf{y}^G_{k+1,j} - \mathbf{y}^G_{k,j}\right),\ k\in\mathcal{T}, j\in\mathcal{G}$$

$$\sum_{\ell=k}^{k+DT-1} (1 - \mathbf{y}^G_{\ell,j}) \ge DT\left(\mathbf{y}^G_{k,j} - \mathbf{y}^G_{k+1,j}\right),\ k\in\mathcal{T}, j\in\mathcal{G}$$




**Key Extensions:** **Stochastic, AC Power Flow (MINLP), Gaming, Contigency**

# Economic Dispatch

## Real-Time Market Clearing

**Sets Locational Marginal Prices (LMPs) in Interconnect**
**Solved Every 5 Minutes, 15 Minutes Foresight**
**Large-Scale LP/QP - $O(10^5\text{-}10^6)$ Continuous, <u>Core</u> of Unit Commitment**

$$\min \sum_{k=\ell}^{\ell+N} \sum_{j \in \mathcal{G}} c_j \cdot G_{k,j}$$

$$\text{s.t. } G_{k+1,j} = G_{k,j} + \Delta G_{k,j},\ k \in \mathcal{T}, j \in \mathcal{G}$$

$$\sum_{(i,j)\in\mathcal{L}_j} P_{k,i,j} + \sum_{i \in \mathcal{G}_j} G_{k,i} = \sum_{i \in \mathcal{D}_j} D_{k,i},\ k \in \mathcal{T}, j \in \mathcal{B}$$

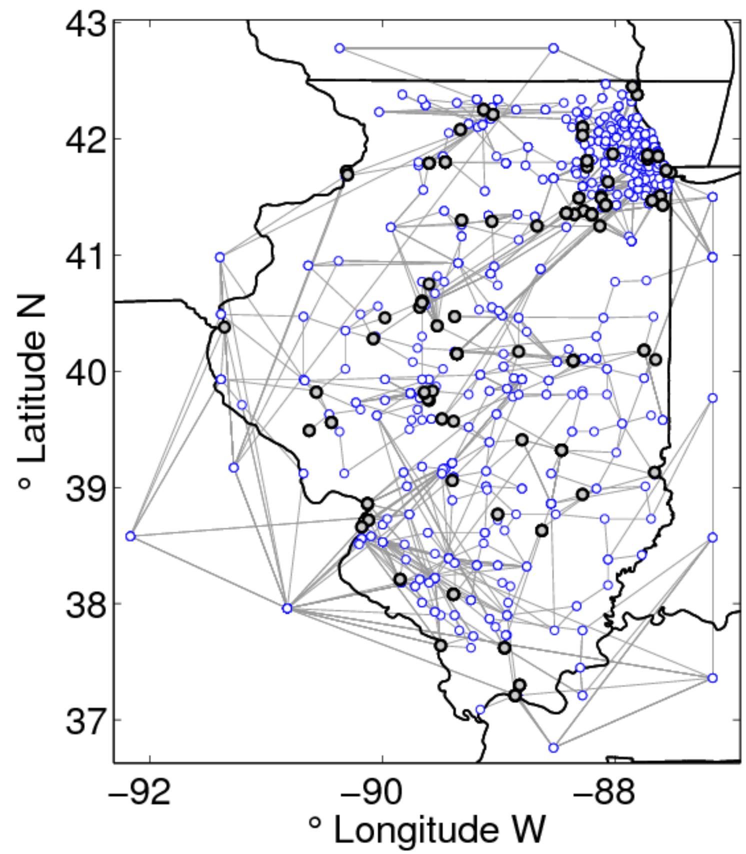
$$P_{k,i,j} = b_{i,j}(\theta_{k,i} - \theta_{k,j}), k \in \mathcal{T}, (i,j) \in \mathcal{L}$$

$$0 \le G_{k,j} \le G_j^{max},\ k \in \mathcal{T}, j \in \mathcal{G}$$

$$0 \le \Delta G_{k,j} \le \Delta G_j^{max},\ k \in \mathcal{T}, j \in \mathcal{G}$$

$$|P_{k,i,j}| \le P_{i,j}^{max},\ k \in \mathcal{T}, (i,j) \in \mathcal{L}$$

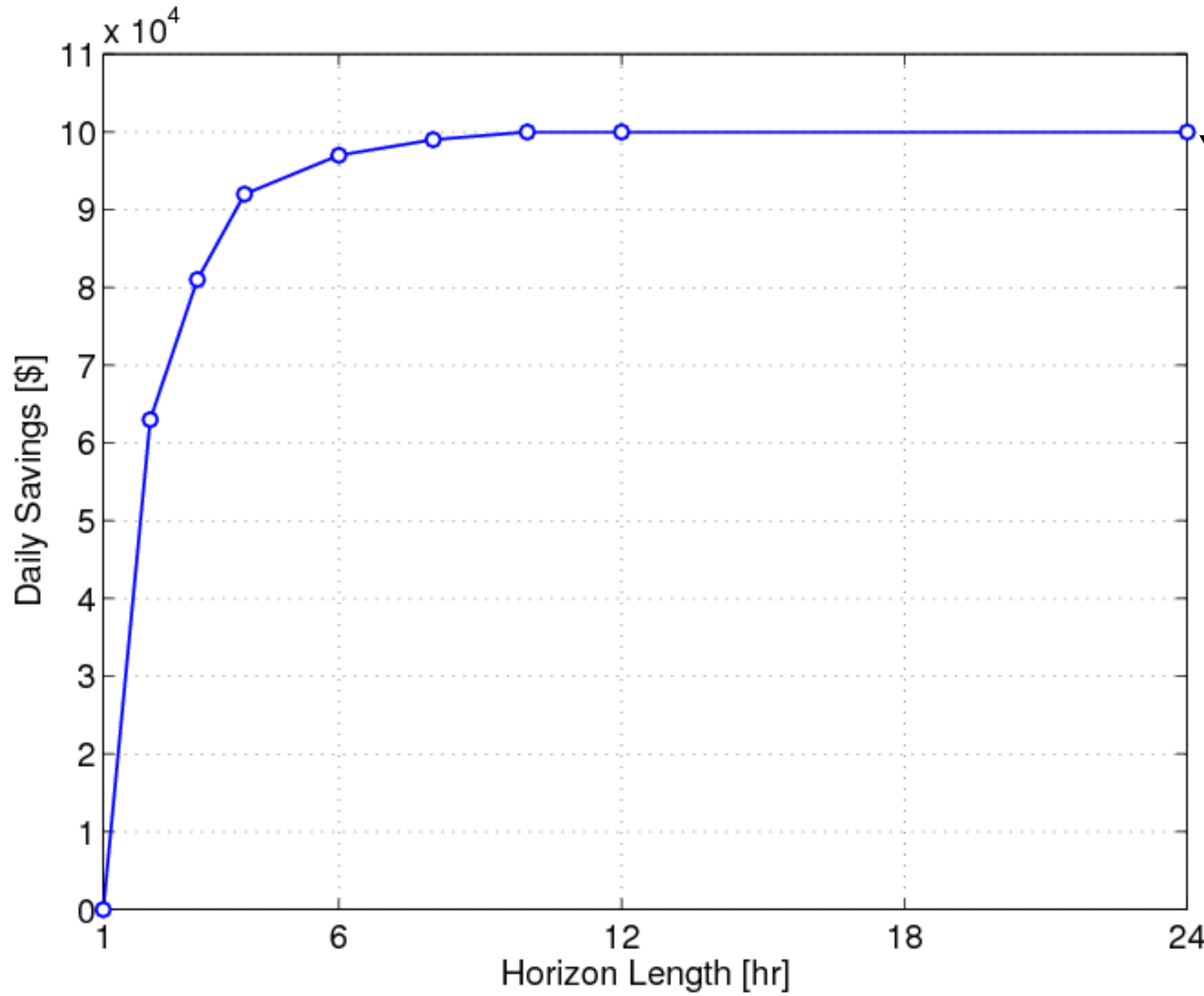
$$|\theta_{k,j}| \le \theta_j^{max},\ k \in \mathcal{T}, j \in \mathcal{B}$$




**Benchmark System –Illinois- 1900 Buses, 2538 Lines, 870 Loads, and 261 Generators**
**Daily Generation Cost ~ $O(10^8)**

# Economic Dispatch

**Effect of Foresight on Costs**




**LP Size**
**105,000 Variables**
**-1 hr/Step-**

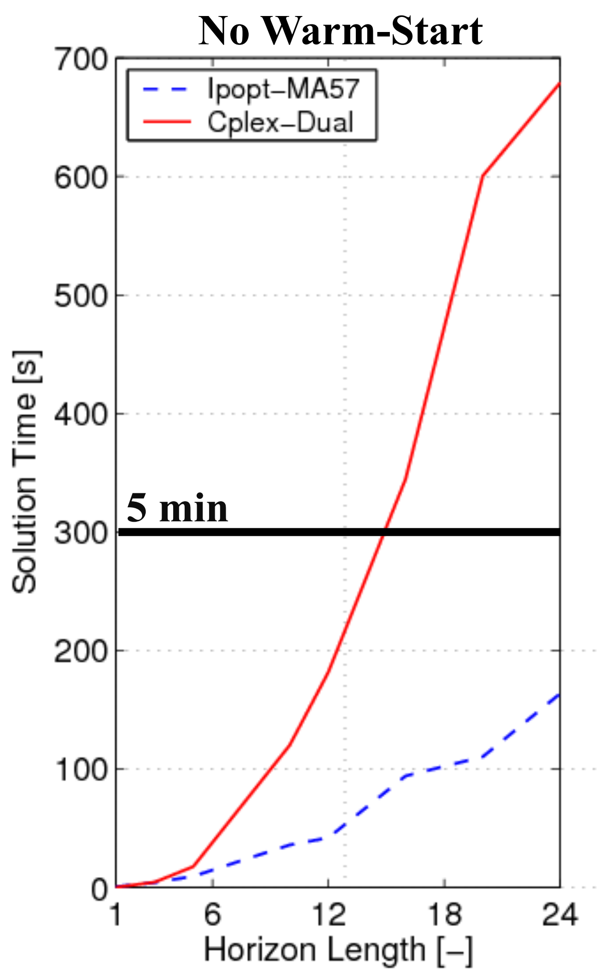
**Potential Savings of $O(10^8)$/Yr – Increase with Wind/Demand Variability**

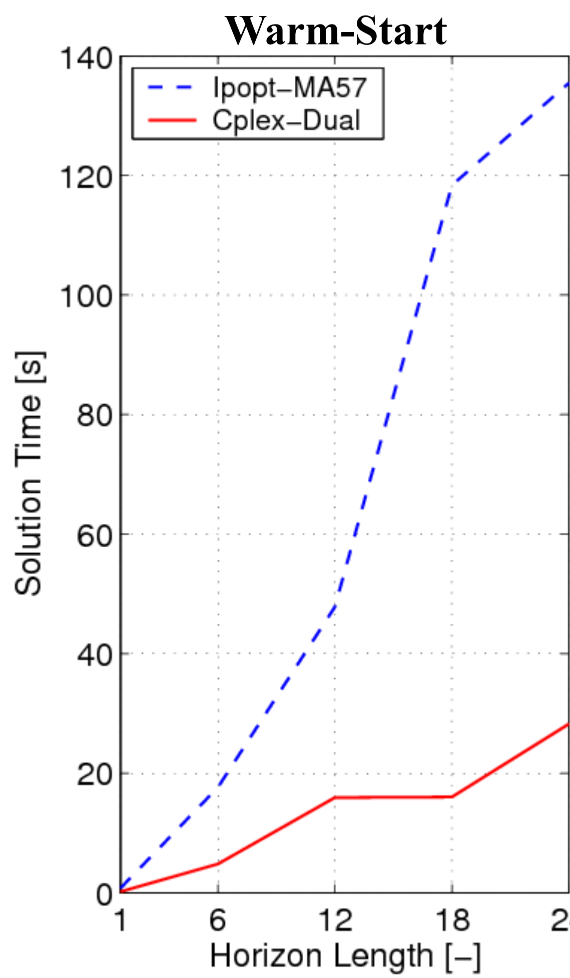
**Savings Constrained by Time Resolution -Desired 5 min-**

# Economic Dispatch

## Computational Performance – Linear Algebra and Warm-Starts

**IPOPT- Symmetric KKT Matrix (MA57) vs. CPLEX-Simplex – Basis Factorization/Updates**




**Basis is "Robust"**

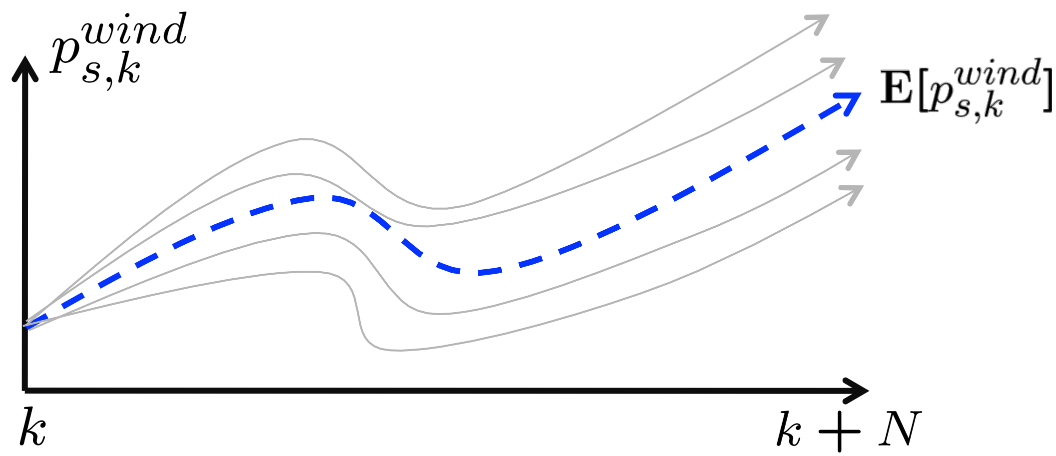
**Warm-Start Strategy - Construct Basis for Simplex -In Advance, With Forecast-**

**Largest Problem Solvable in 5 Minutes - 20 Hr Foresight, 240 Steps, 5 Min/Step, $1 \times 10^6$ Variables**

# Stochastic Economic Dispatch

**Uncertainty Handled Through <u>Reserves</u>** **-Currently 10% of Demand-Conservative & Expensive**

**Stochastic Optimization Can Make Reserves Adaptive** **- e.g., Day-Night Wind/Demands**




**1st Stage**
**<u>Current</u> Demands and Wind**

**2nd Stage**
**<u>Future</u> Demands and Wind**

$$\min \quad f(x) + \frac{1}{S}\sum_{i=1}^{S} g_s(y_s)$$

$s.t.$

$$\begin{array}{lllllll}
A_0 x & +B_0 y_0 & & & & & = b_0 \\
A_1 x & & +B_1 y_1 & & & & = b_1 \\
A_2 x & & & +B_2 y_2 & & & = b_2 \\
\vdots & & & & \ddots & & \vdots \\
A_S x & & & & & +B_S y_S & = b_S \\
\end{array}$$

$$x, y_0, y_1, y_2, \ldots, y_S \geq 0$$

**Main Bottlenecks : Number of 1st Stage Variables, Scenarios, Block Size**

# Stochastic Economic Dispatch

## PIPS, IPOPT, OOPS:

**Barrier, Coarse Linear Algebra Decomposition, Distributed Memory**

**PIPS: OOQP** *Gertz & Wright*, **Schur Complement-Based, Dynamic Load Balancing**

- **Bottlenecks and Latency of Forming and Factorizing Schur Complement Avoided with Iterative Solver and <u>Stochastic Preconditioner</u>** *Petra & Anitescu, 2010a*

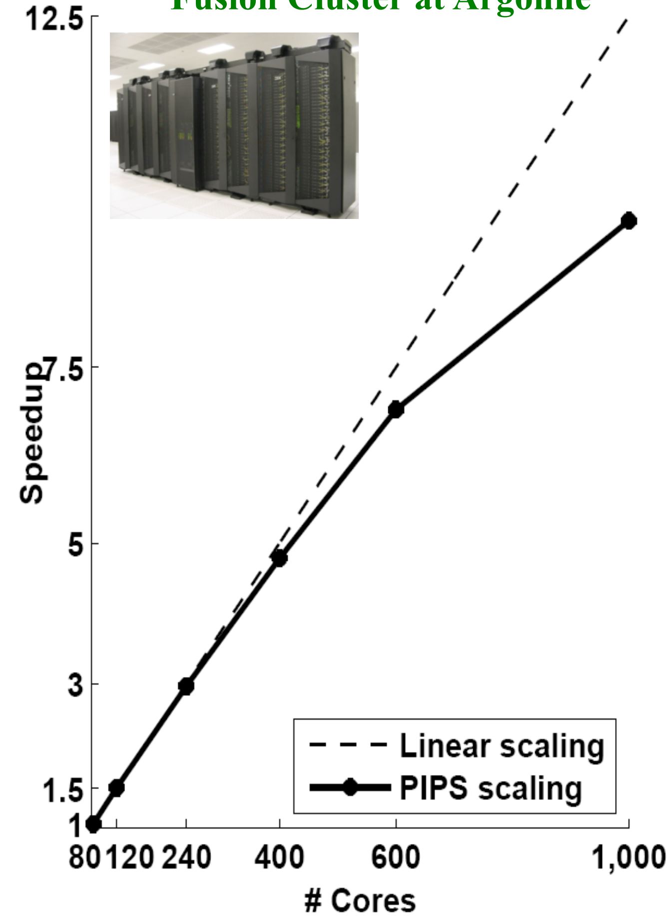
- **Problem with O($10^7$) Variables (No Network) - <u>600</u> Times Faster Than Serial on 1,000 cores**

- **Strong Scaling on 2,000 cores with O($10^8$) Total Variables and O($10^5$) First-Stage Variables ScaLAPACK** *Petra & Anitescu, 2010b*

- **However, Speed-ups not Enough for Use in MILP**

- **Key Questions:**
  - **Fine-Grained Parallelism**–**Network, Multi-Core, BlueGene-**
  - **Is Probability Distribution Correct?**
  - **What if Scenario Generation is Expensive?**

**Fusion Cluster at Argonne**



# Uncertainty Quantification

**Major Advances in Meteorological Models (WRF)**

**Highly Detailed Phenomena - PDEs**

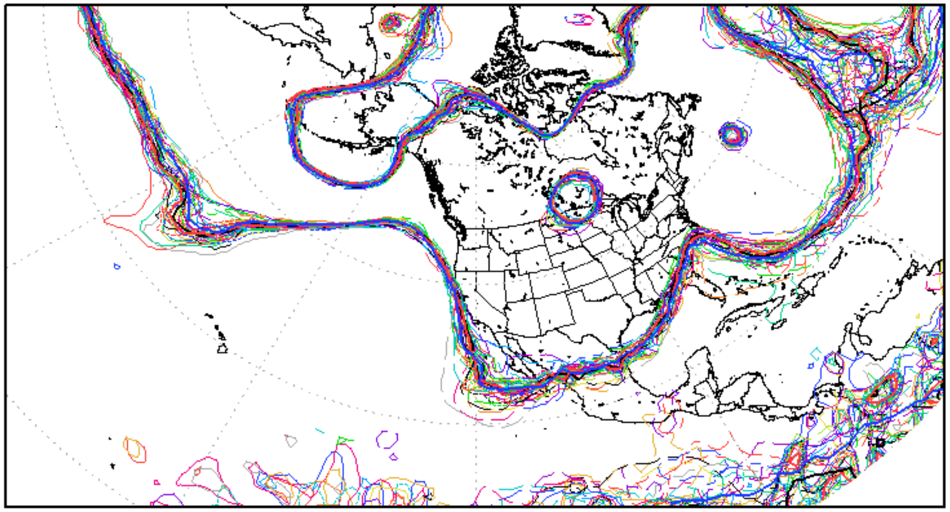
**High Complexity 4-D Fields ($10^6$- $10^8$ State Variables)**

**Model Reconciled to Measurements From Meteo Stations**

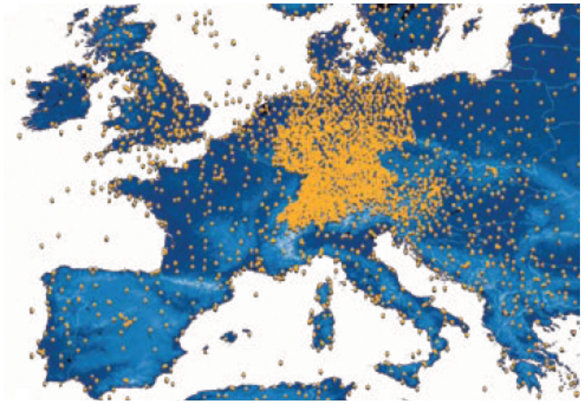
**Data Assimilation Every 6-12 hours:**

**Optimization Based : 3-D Var** *Courtier, et.al. 1998,* **4-D Var** *Navon et.al., 2007*

**Simulation Based : Ensemble Kalman Filter** *Eversen, et.al. 1998*



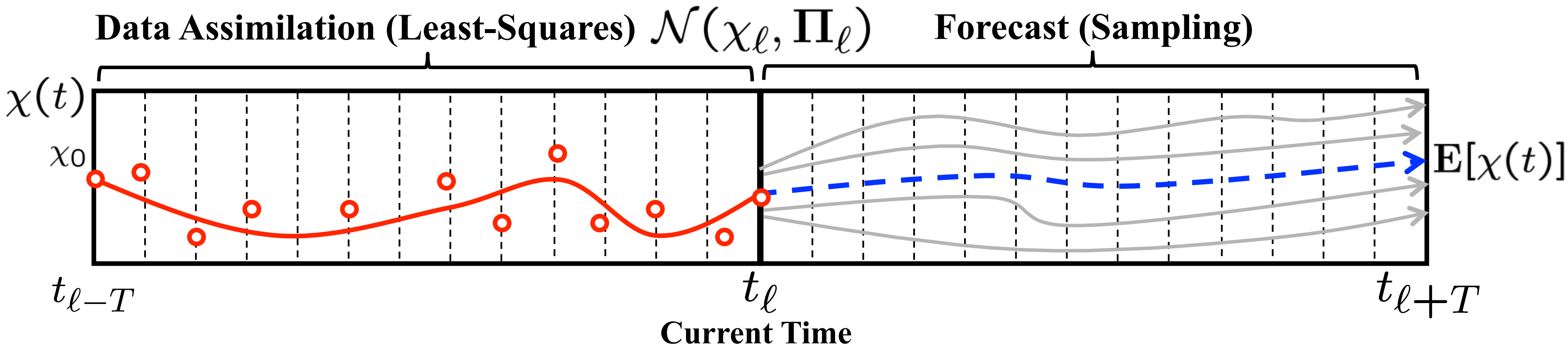
***http://www.emc.ncep.noaa.gov/gmb/ens/***



***http://www.meteomedia.com/***

**Is WRF Computationally Practical Enough for Market Operations?**

# Uncertainty Quantification




**Forming Covariance Matrix is <u>Impractical</u> -Size of State Space-** *Constantinescu, et.al. 2009*

**1) Use <u>Only</u> Most Relevant States (Adjoint Analysis)**

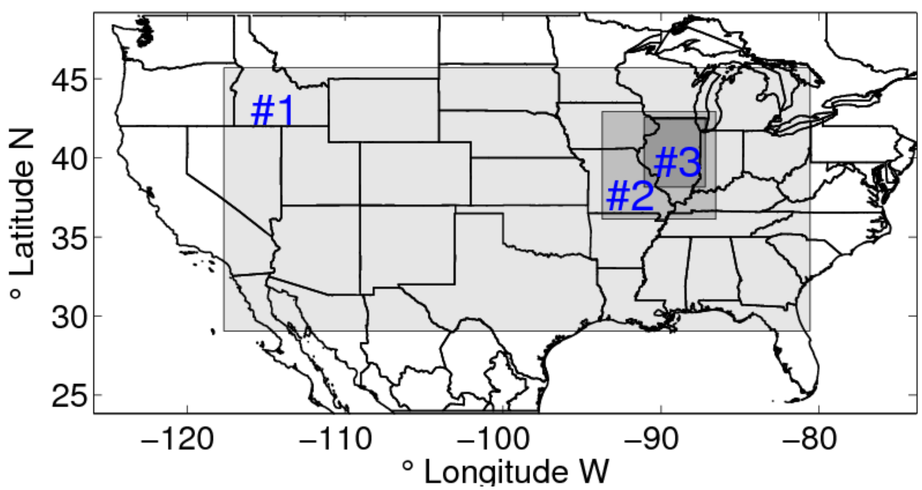
**2) Propagate Samples through WRF Model**

| ID | Size | Grid |
|---|---|---|
| #1 | $130 \times 60$ | $32\,\mathrm{km}^2$ |
| #2 | $126 \times 121$ | $6\,\mathrm{km}^2$ |
| #3 | $202 \times 232$ | $2\,\mathrm{km}^2$ |

**Making WRF Computationally Feasible**

**<u>Grid-Targeted</u> Resolutions and Computational Resources**

| CPUs | Wall-time [hr] |
|---|---|
| 4 | 50 |
| 8 | 28 |
| 16 | 17 |
| 32 | 10 |

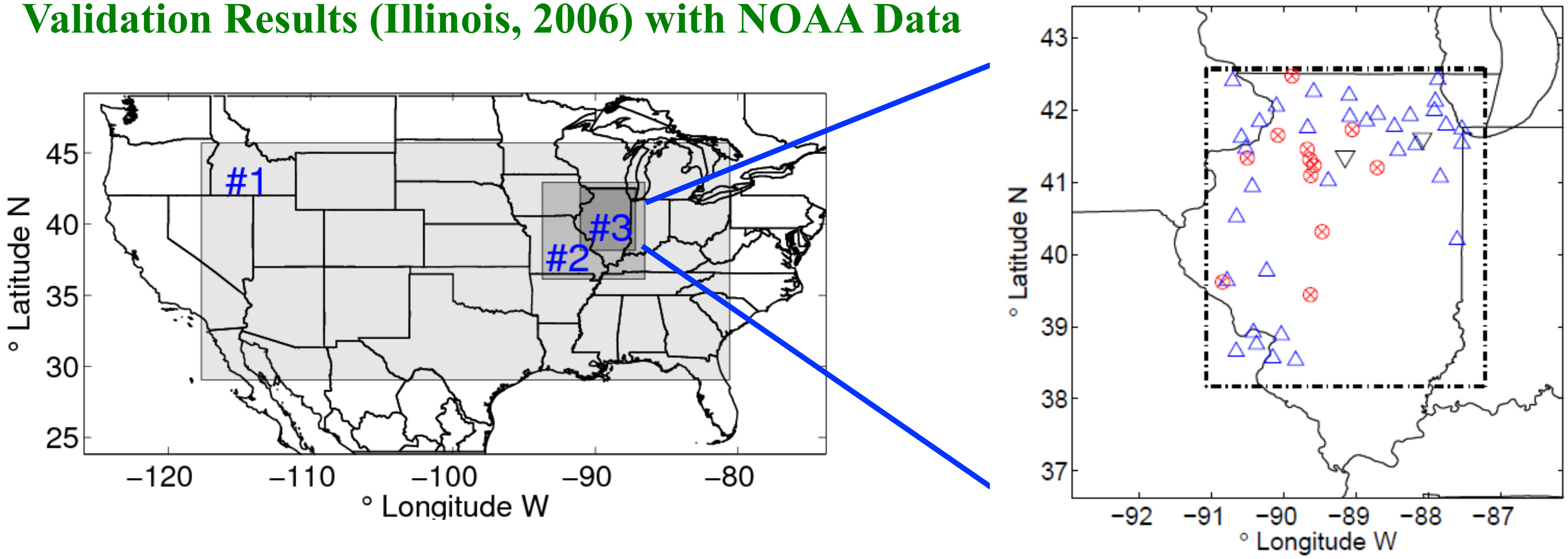


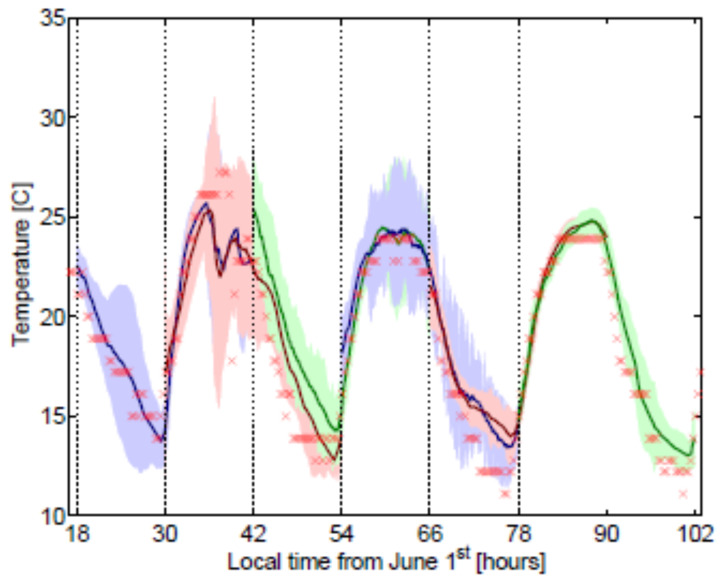

**Jazz Cluster at Argonne National Laboratory**

- ✔ Illinois [2km]: 500 processors
- ☐ US [2 km]: ~50,000 processors
- ☐ US [1 km]: ~400,000 processors

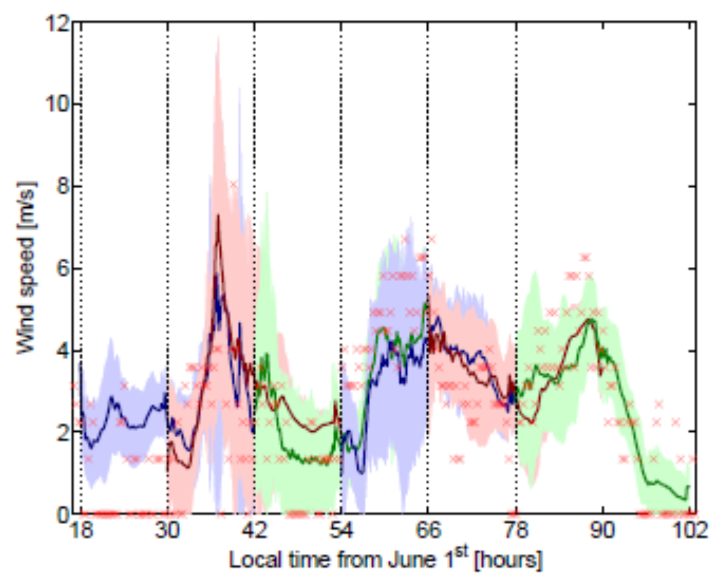
# Uncertainty Quantification

**Validation Results (Illinois, 2006) with NOAA Data**



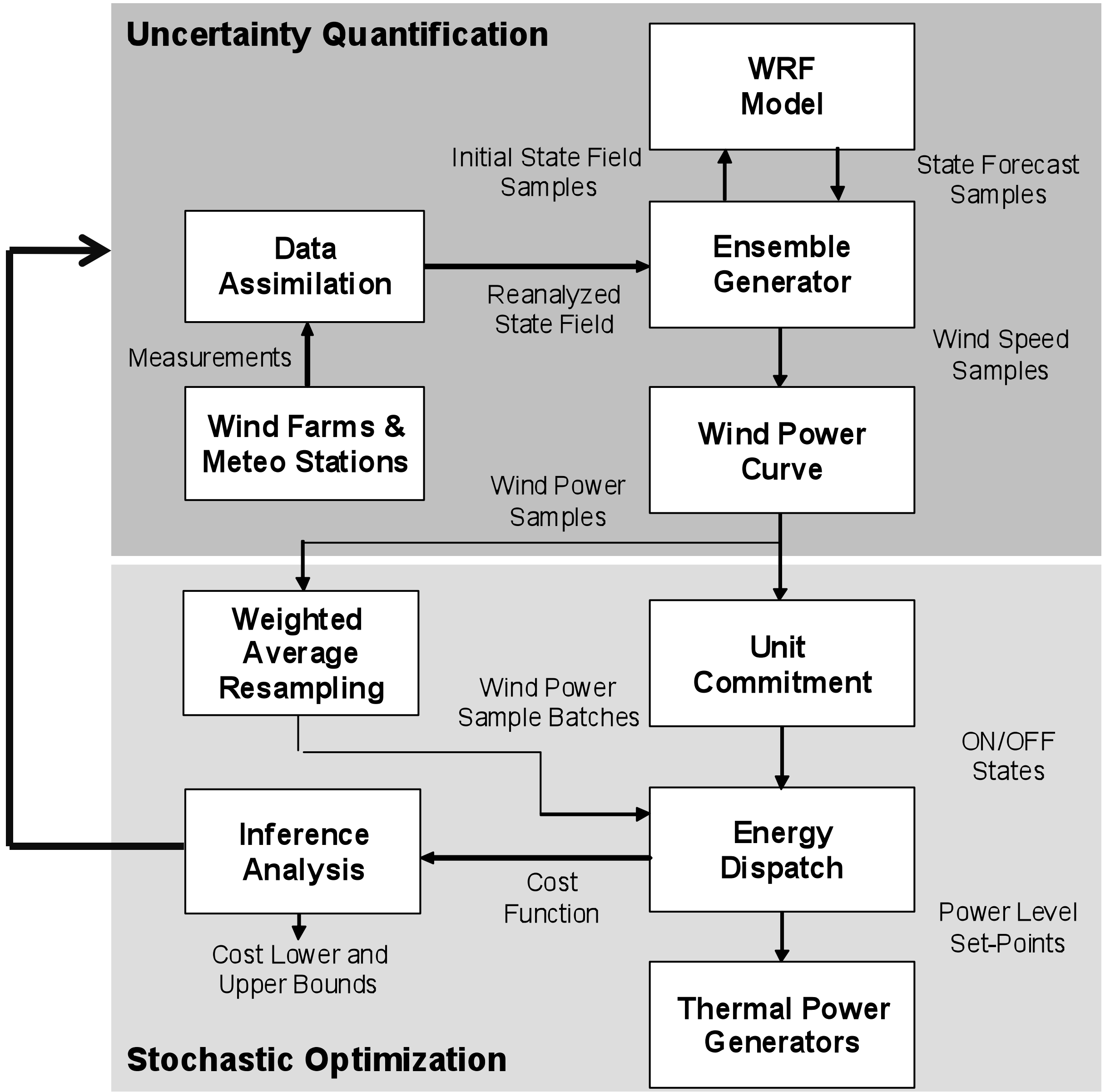




**Temperature [°C]**




**Wind Speed [m/s]**

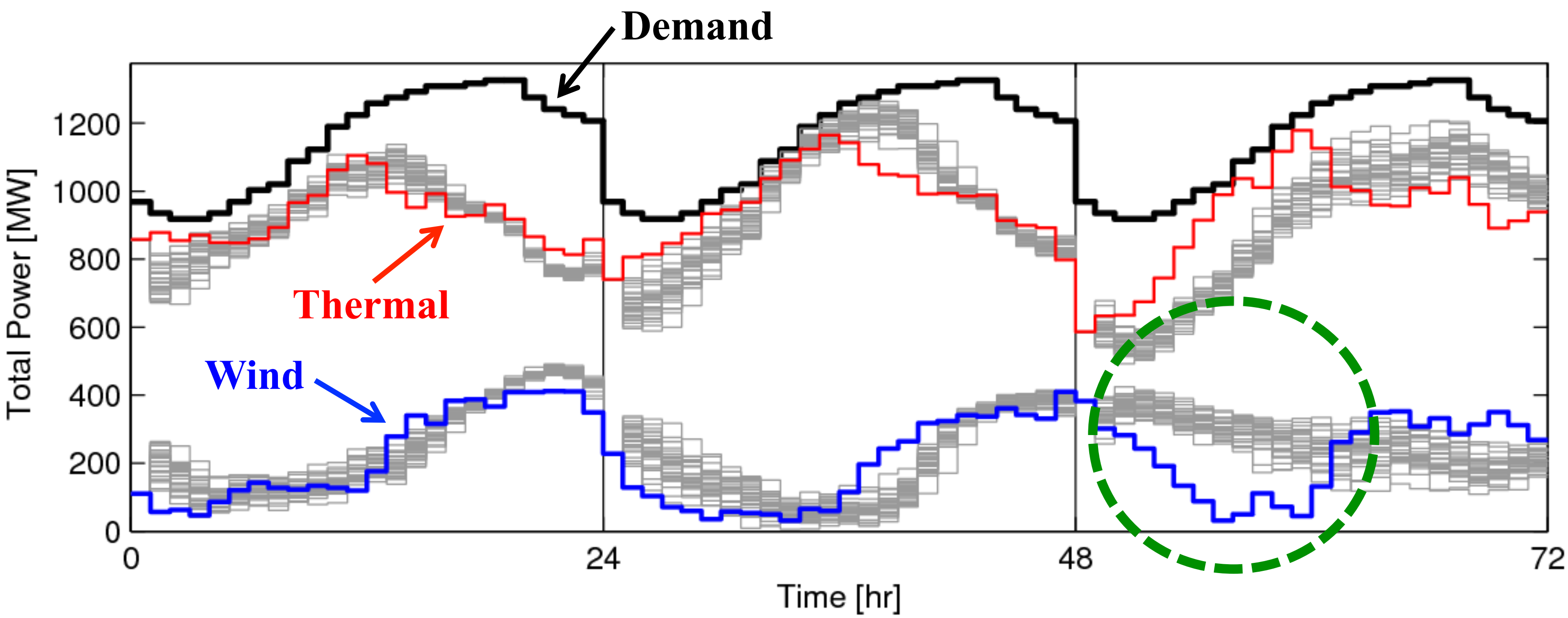
# Stochastic Optimization and Uncertainty Q




**Key: Probability Distribution and Number of Samples Must be Adapted in Real-Time**

# Stochastic Optimization and Uncertainty Q

## Aggregated Power Profiles -Validation with Real Data-




**- WRF Forecasts are -In General- Accurate with Tight Uncertainty Bounds**

**- Inference Analysis Reveals that 30 WRF Samples are Sufficient**

**Cost ~ \$474,000, Upper Bound $\sigma^2$ (1,082 $\$^2$), Lower Bound $\sigma^2$ (1,656 $\$^2$)**

**- Excursions Do Occur: Probability Distribution of 3rd Day is Inaccurate!**

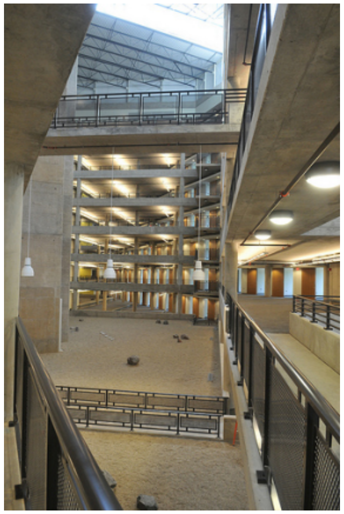
**Higher Frequency Data Assimilation (1 hour)? Missing Physics? 100m Sensors?**

**Key Area: Real-Time Algorithms for Data Assimilation**

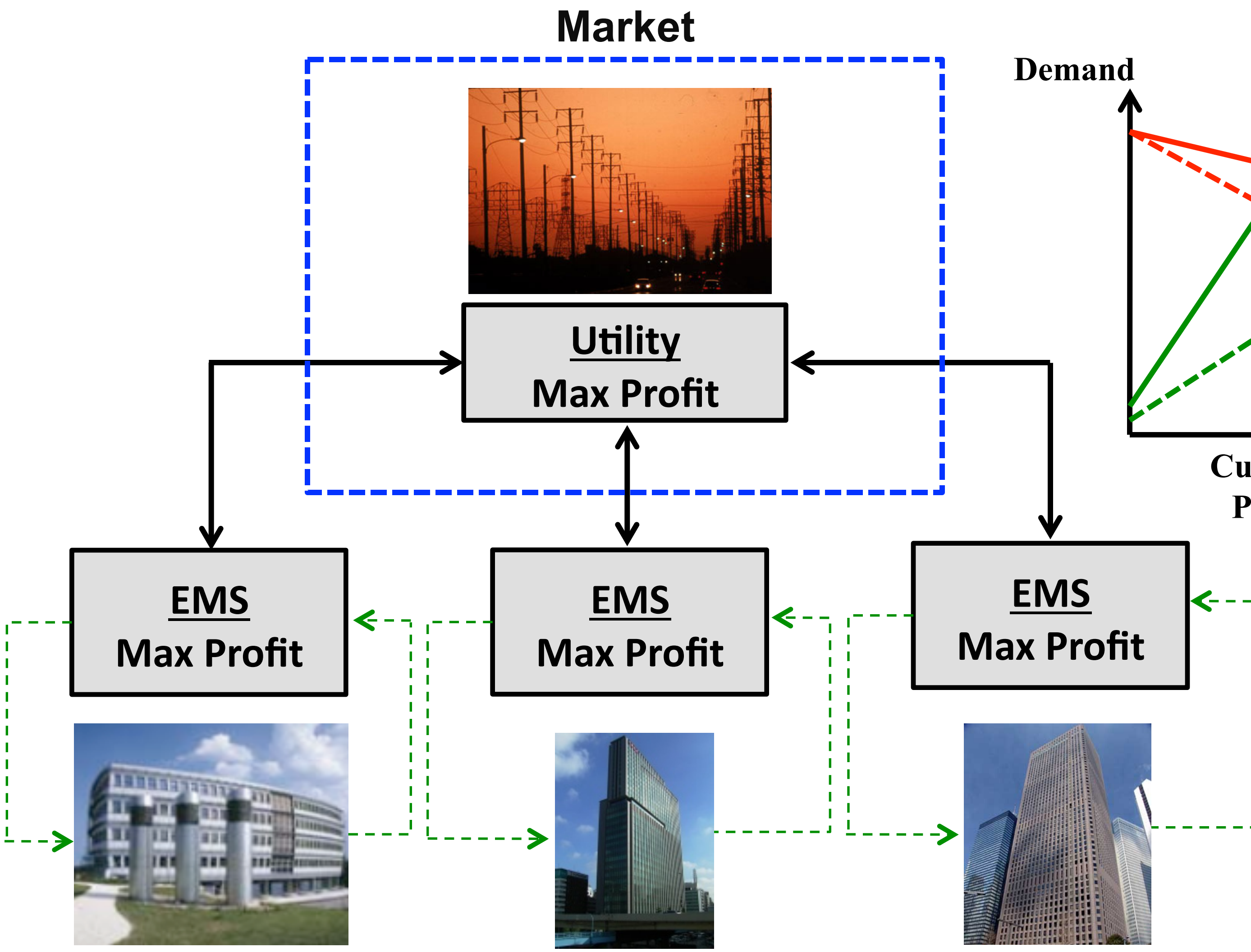
# Building Energy Management

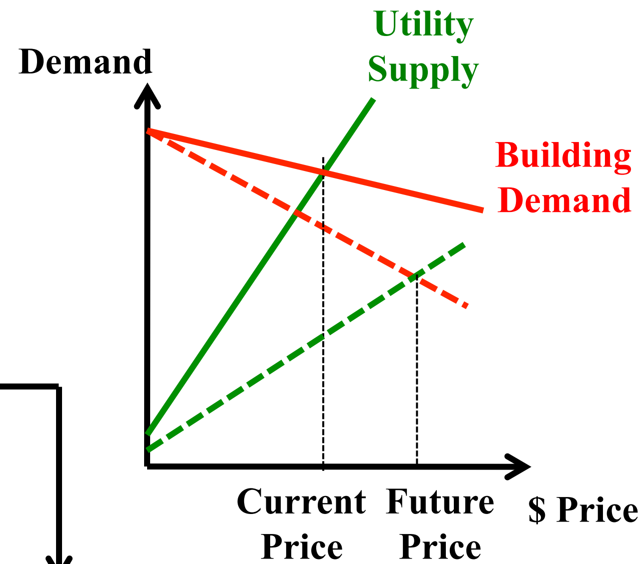
## Collaborative Project: Argonne-Building IQ
## "Proactive Energy Management for Building Systems"

Mike Zimmermann, Tom Celinski, Peter Dickinson (BIQ), and Victor M. Zavala (ANL)



# Building Energy Management



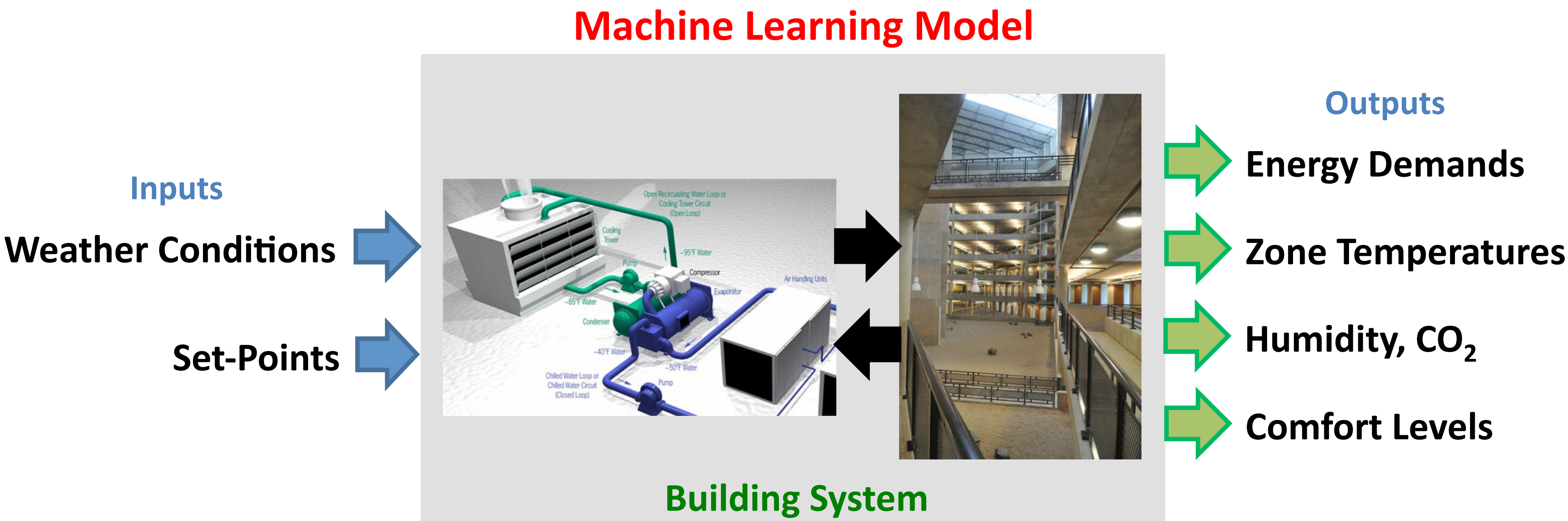




~ 50% of U.S. Energy Resources -Gas, Electricity- Go to HVAC

EMS Needs to Forecast & Optimize Demand as a Function of Weather and Market Prices

Management of New Technologies (Batteries, PHEVs, Photovoltaic, Demand-Response)

# Building Energy Management




- **Real-Time Optimal Control Problem with Machine Learning Model -NLP-**
  - Solved Every 10 Minutes, Foresight of 2 Hours
  - Building Model Re-Trained Daily
  - Machine Learning Key for Large-Scale and Cheap Deployment

- **Trade-Off:** Comfort vs. Energy Demands vs. $CO_2$ emissions

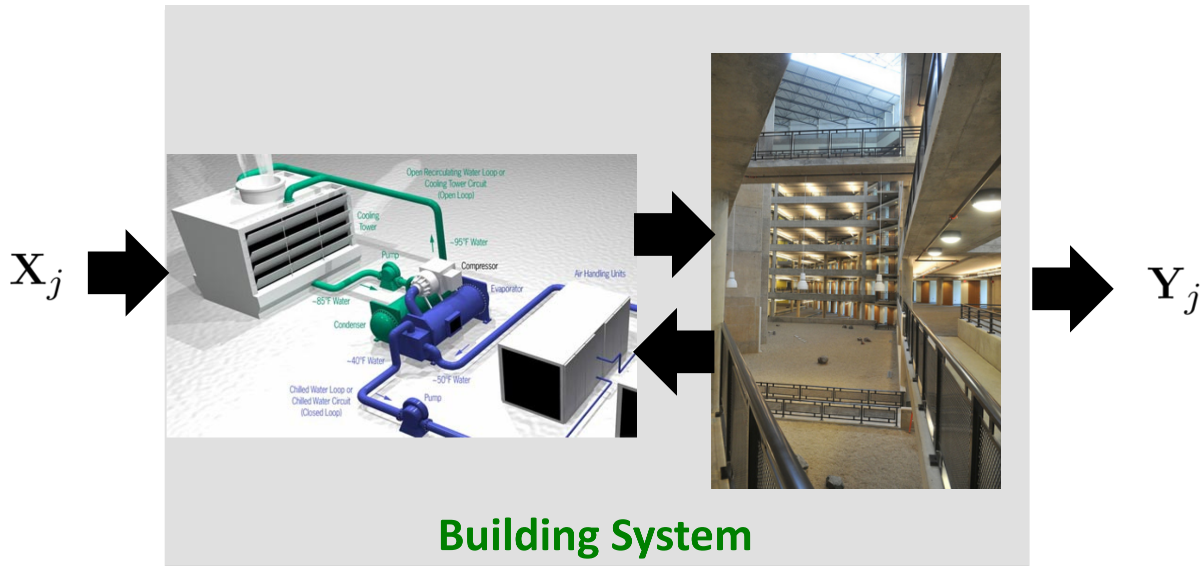
- **Exploit Sensor Information:** Occupant Tracking, Disaggregate Demands

# Building Energy Management

## Occupant Tracking, TCS Building at Argonne *Skow, Domagala, Cattlet. 2010*

# Machine Learning

**Gaussian Process (GP) Modeling** *Rasmussen, et.al. 2001*




**1. Input-Output Data Sets:** $\mathbf{X}_j, \mathbf{Y}_j$

**2. Covariance Structure :** $\mathbf{V}(\mathbf{X}_j, \mathbf{X}_i, \eta) := \eta_0 + \eta_1 \cdot \exp\left(-\frac{1}{\eta_2}\|\mathbf{X}_j - \mathbf{X}_i\|^2\right)$

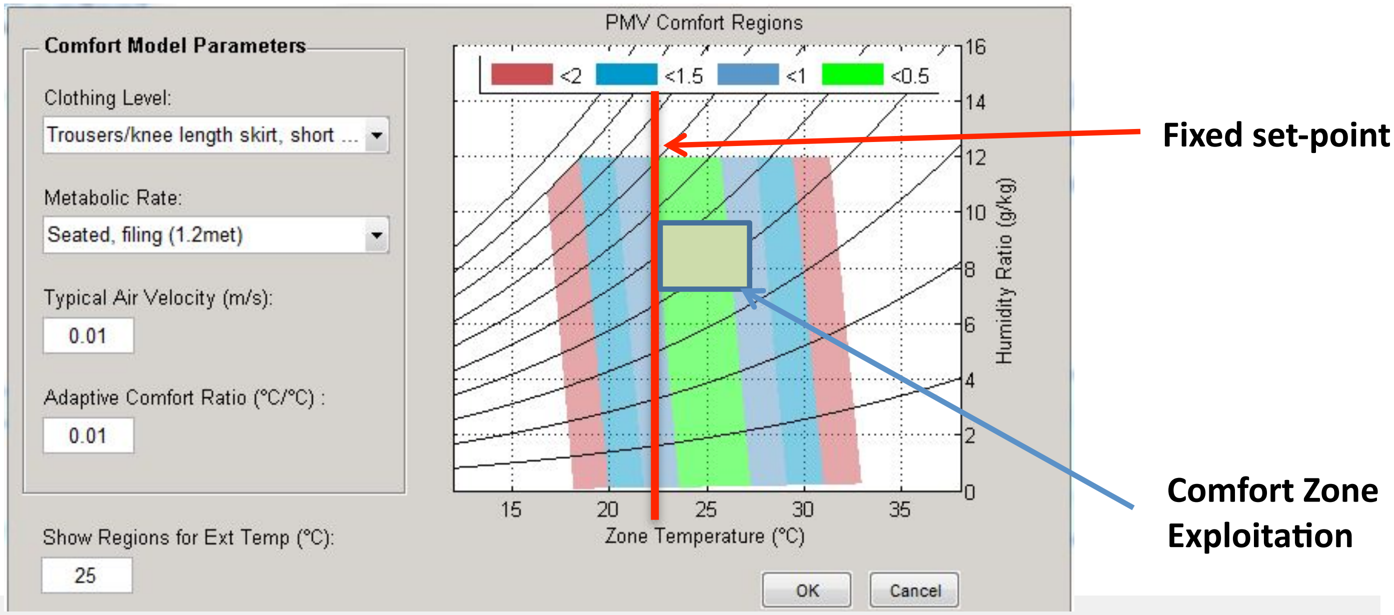
**3. Apply Maximum Likelihood:** $\log p(\mathbf{Y}|\eta) = -\frac{1}{2}\mathbf{Y}\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta)\mathbf{Y} - \frac{1}{2}\log\det(\mathbf{V}(\mathbf{X},\mathbf{X},\eta))$

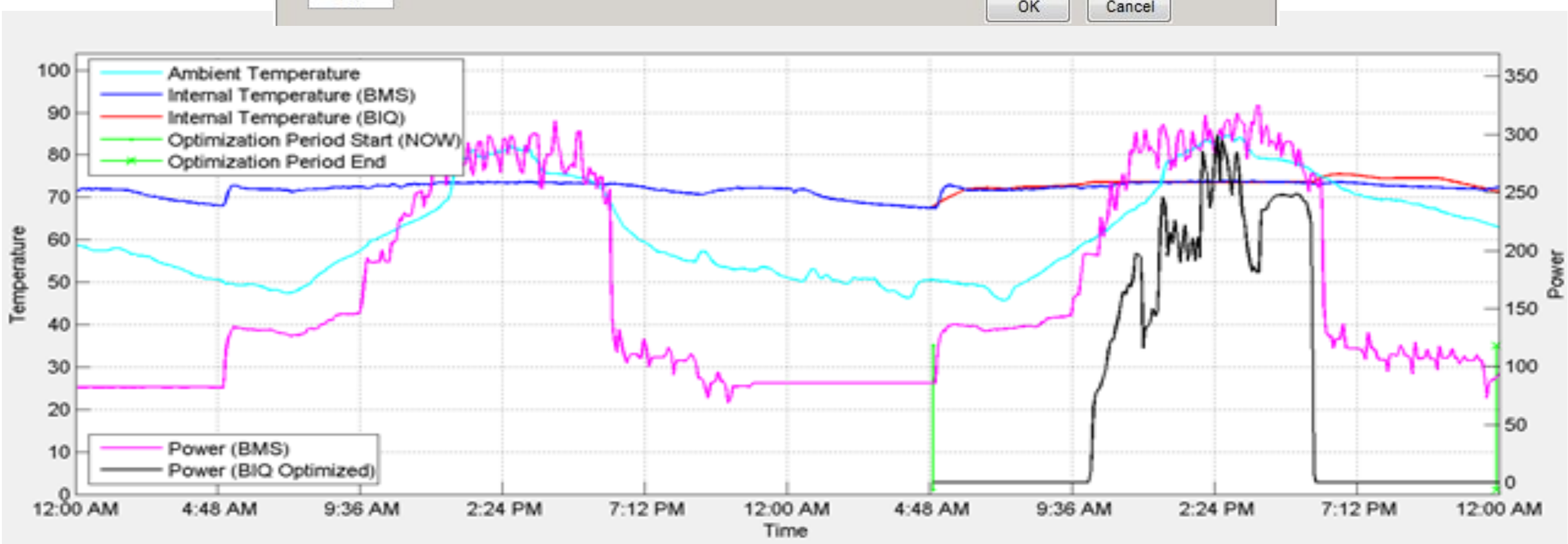
**4. Posterior Distribution:** $\mathbf{Y}^P = \mathbf{V}(\mathbf{X}^P, \mathbf{X}, \eta^*)\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta^*)\mathbf{Y}$ **Forecast Mean**

$\mathbf{V}^P = \mathbf{V}(\mathbf{X}^P, \mathbf{X}^P, \eta^*) - \mathbf{V}(\mathbf{X}^P, \mathbf{X}, \eta^*)\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta^*)\mathbf{V}(\mathbf{X}, \mathbf{X}^P, \eta^*)$ **Covariance**

**Key Challenge: Handling Covariance Matrix -Large, Nonlinear, and Dense-**

# Building Energy Management

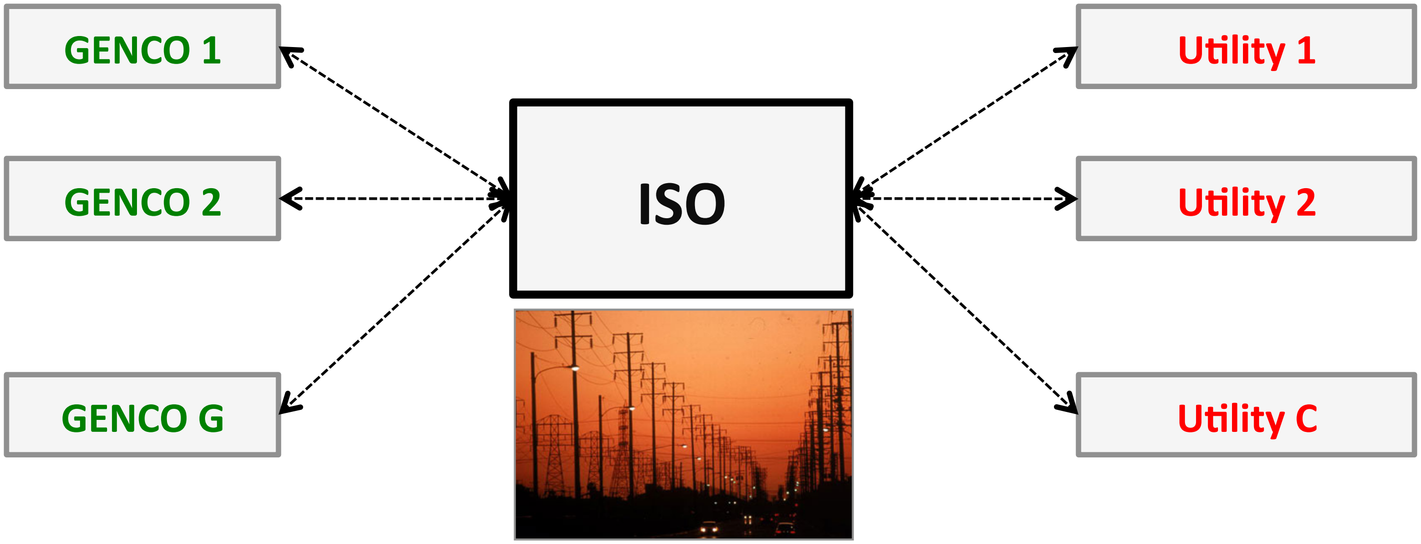



**BuildingIQ EMS Implemented at Argonne's TCS Building**

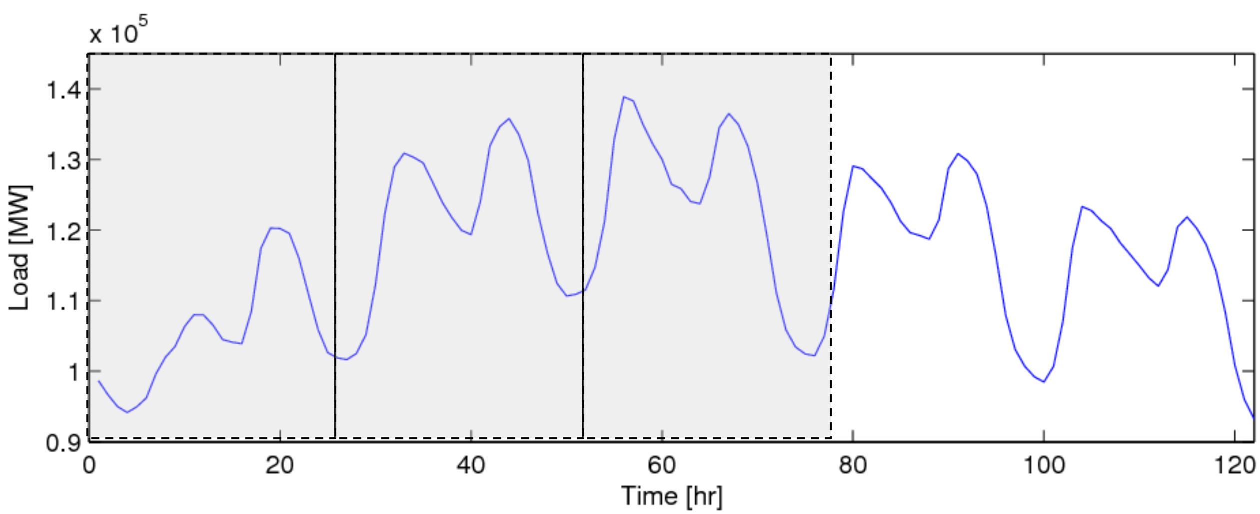
**Expected Yearly Savings of ~30% on HVAC Energy – \$O($10^5$)**

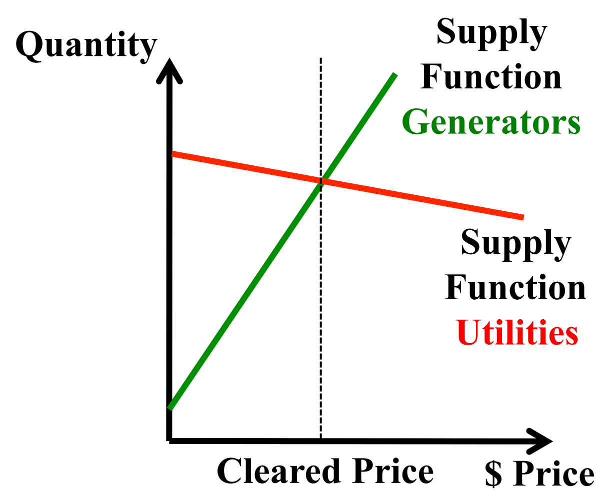
# Dynamic Electricity Markets




**- GENCOs and Utilities <u>Bid</u> in Day-Ahead and Real-Time Markets**

**- ISO Clears Markets To <u>Maximize Social Welfare</u>**




**Generator States are Propagated in Time – Ramps and Foresight Affect <u>Market Stability</u>**

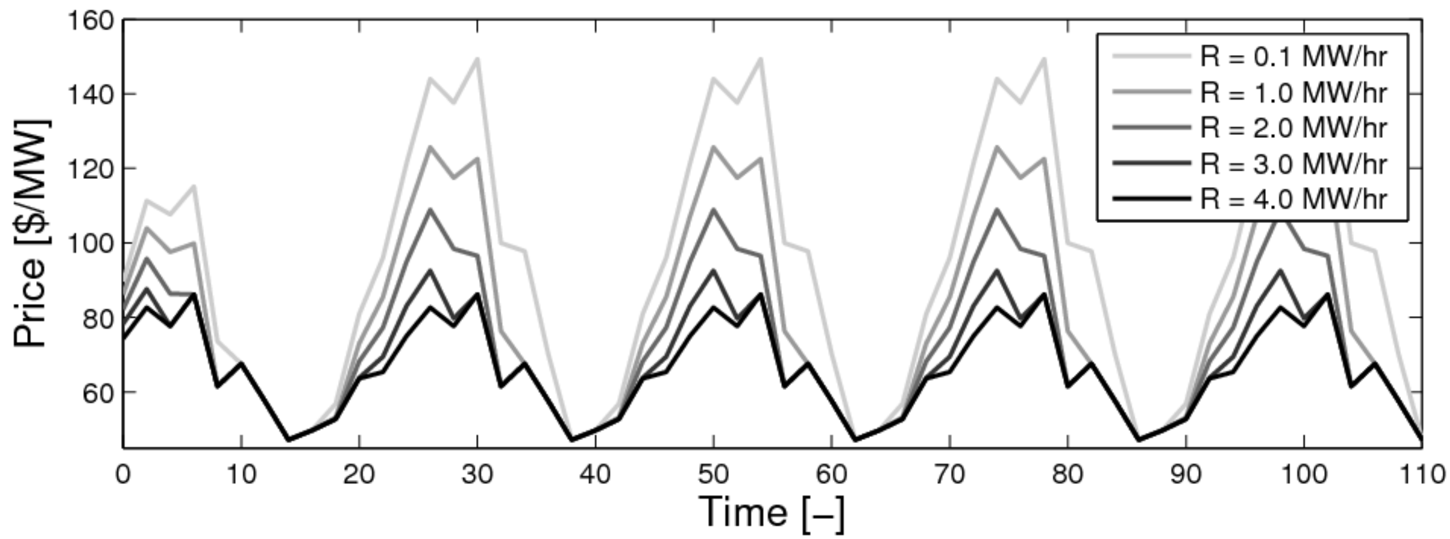
# Dynamic Electricity Markets

**Supply Function-Based Dynamic Game Models** *Kannan & Z., 2010*

**- Linear Complementarity Problem: Economic Dispatch (LP) + GENCOs (LP)**

$$\left.\begin{array}{l}
\displaystyle \max_{a_i^t, b_i^t, q_i^t} \quad \sum_{t=1}^{T} \left( \overbrace{\left( \frac{q_i^t + a_i^t}{b_i^t} \right)}^{\text{Price}} q_i(t) - C_i(q_i(t)) \right) \\
\left\{ s.t. \quad \begin{array}{l} q_i^t \le cap_i^t \\ q_i^{t+1} - q_i^t \le R_i^t \\ \frac{q_i^t + a_i^t}{b_i^t} = \frac{c^t + \sum_{i=1}^N a_i^t}{d^t + \sum_{i=1}^N b_i^t} \\ q_i^t \ge 0 \end{array} \right\} , \underbrace{\forall t = 1, 2, .., T}_{\text{Horizon}}
\end{array}\right\} \underbrace{\forall i = 1, ..., P}_{\text{Players}}$$

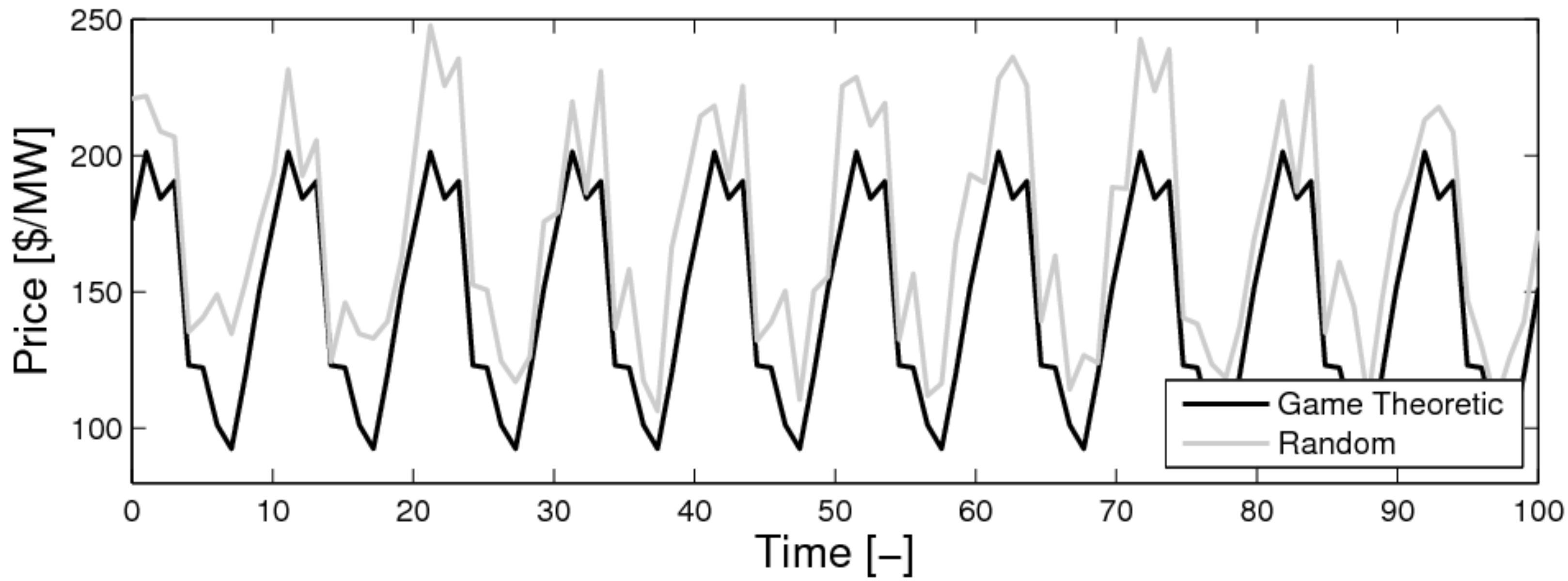
**Effect of Ramp Constraints on Market Equilibrium**



# Dynamic Electricity Markets

**Identifying Non-Gaming Behavior**

**Some Players -Intentionally or Unintentionally- Bid Suboptimally**
**Introduces <u>Noise</u> in Equilibrium – Can be Inferred from Data**




**Huge Potential for Dynamic Market Models**

- **Mechanistic Price Forecasting, Interconnect Level Transactions**
- **Fundamental -Market Stability- and Algorithmic Questions -Incomplete Gaming-**
- **Extensions to Integers Needed: Unit Commitment + GENCOs Problems, Interconnects**

# 3. Conclusions

# Conclusions

**Next-Generation Power Grid**

- **Higher Frequency Dynamic Forcings**
- **Market Decentralization**
- **Huge Savings -Emissions, Prices-**

**Optimization Needs**

- **Distributed Algorithms for Games (LP/QP,MILP)**
- **Fast Algorithms for Machine Learning and Data Assimilation**
- **Capturing Physics in Markets – AC Power Flow, NLP, MI(N)LP**
- **Linear Algebra : Fine-Grained Parallelism, Alternatives to Simplex and Barrier**
- **Realistic Models and Testing (Closed-Loop) for Benchmarking**

**Other Areas**

- **Integration of Electricity, Water, and Natural Gas Markets** *Shahidehpour, et.al. 2009*
- **Sensor Design, Placement, and Observability - Grid, Buildings –**
- **Contigency Analysis** *Pinar, et.al. 2010*

# Optimization Challenges in Energy Systems

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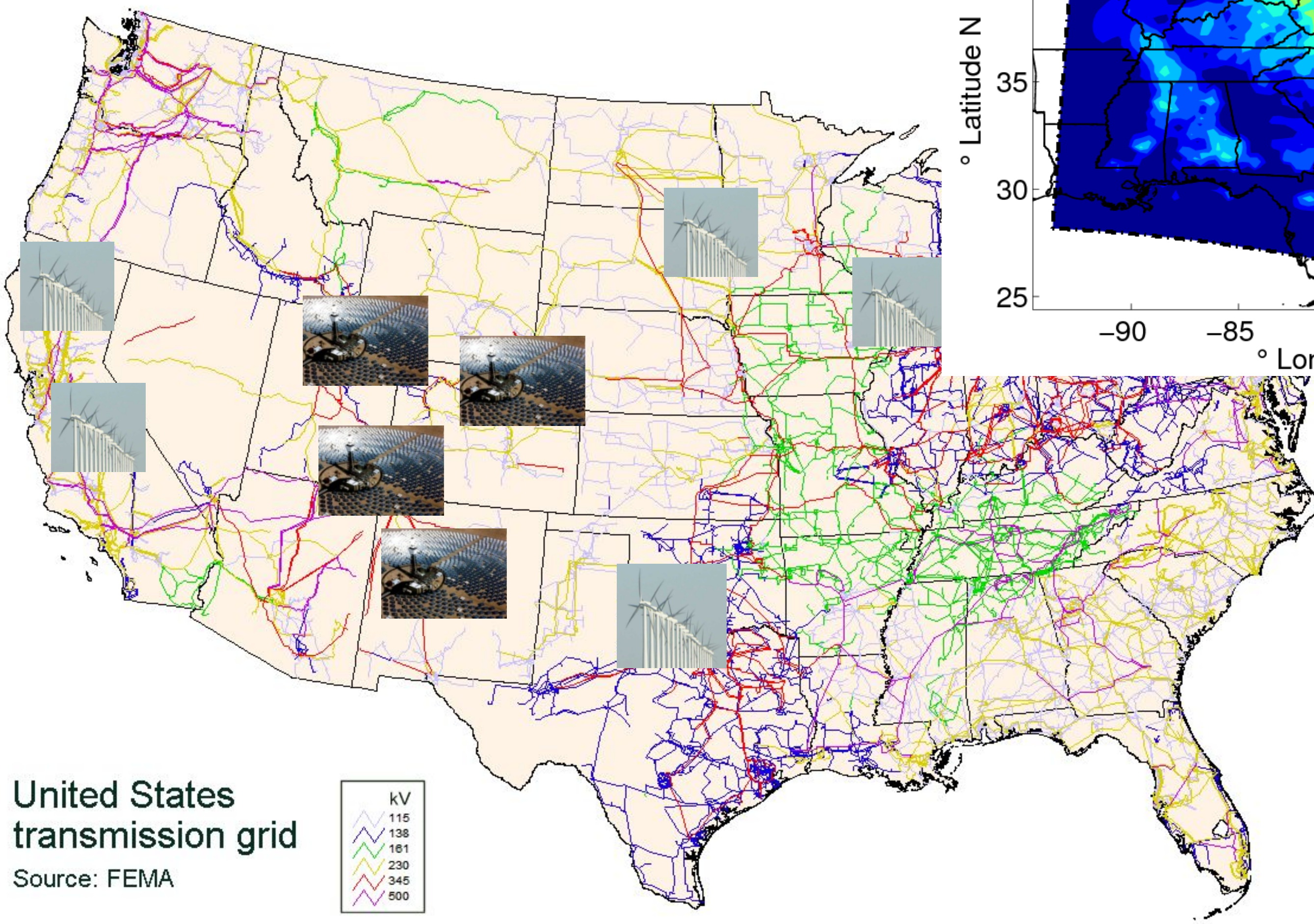
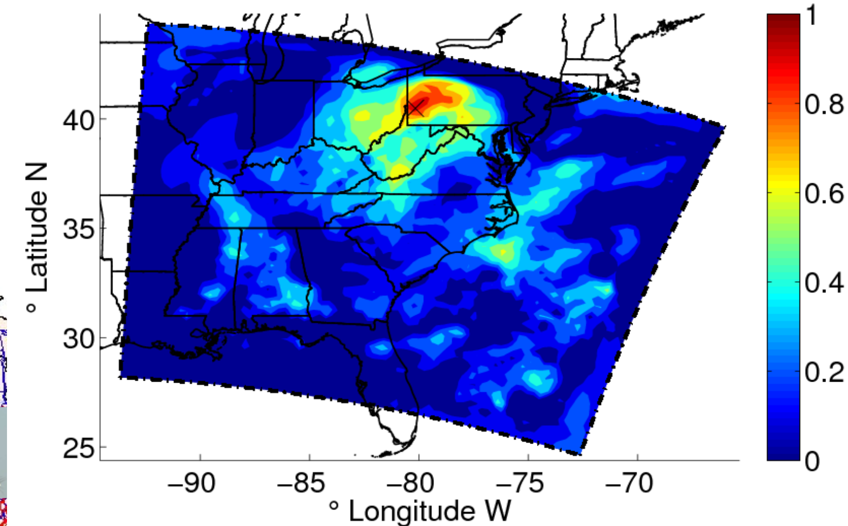
**M.Anitescu, E.Constantinescu, S.Leyffer, C. Petra, A. Kannan**

**US-Mexico Workshop on Optimization and its Applications**
**January 3rd, 2011**

# Motivation




**Weather, Demands, and Generation Exhibit Complex Spatio-Temporal Correlations**

**Correlations Must Be Captured For Efficient Forecasting**

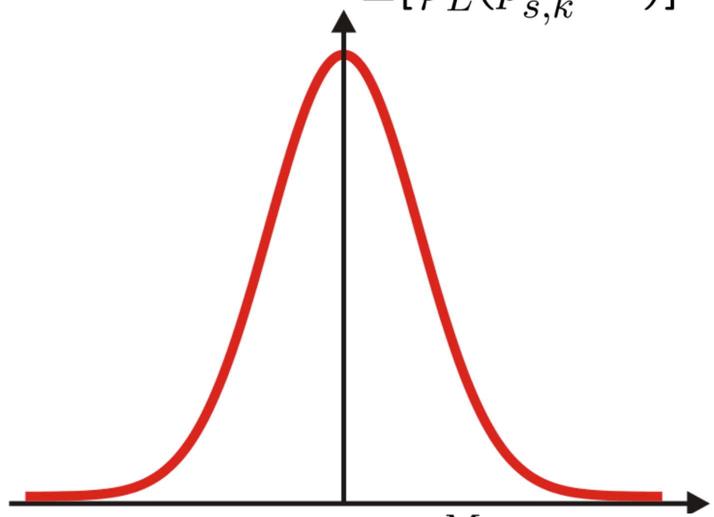
# Inference Analysis

## Integration Uncertainty Quantification and Stochastic Optimization

- Forecast Probability Distribution is NOT in Closed-Form
- Generating Each Sample is Expensive : 50-100 Practical

**Cost Confidence Intervals**

$$\mathbf{E}[\varphi_L(p_{s,k}^{wind,\ell})] \approx L_M := \frac{1}{M}\sum_{j=1}^{M}\varphi(p_{s,k}^{wind,\ell})$$



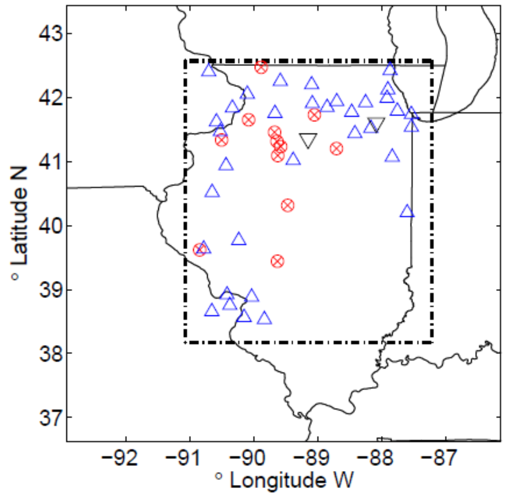
$$\mathbf{Var}[\varphi_L(p_{s,k}^{wind,\ell})] \approx \frac{1}{M-1}\sum_{j=1}^{M}(\varphi(p_{s,k}^{wind,\ell}) - L_M)^2$$

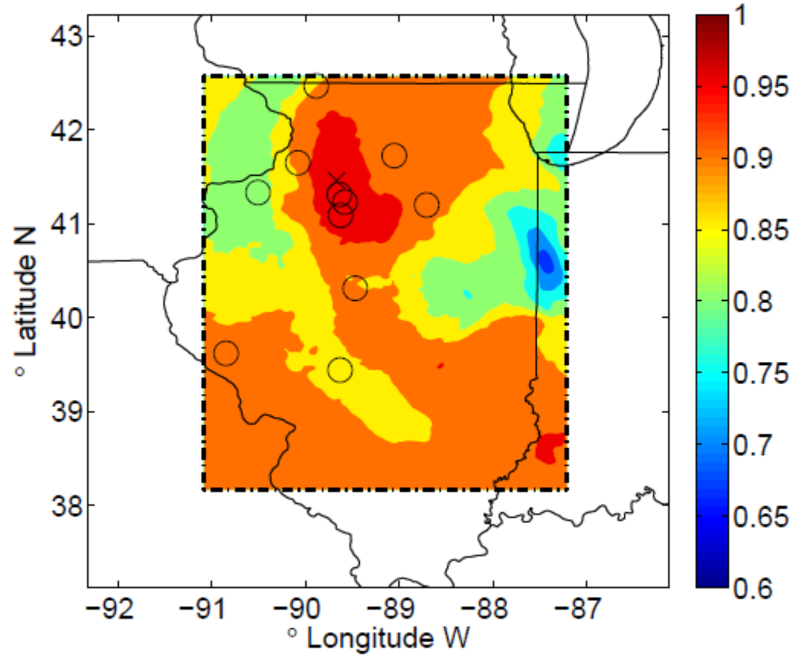
## How to Generate More Samples?

1) Sample Weights on Hyperplane $\sum_{s\in\mathcal{S}} w_{s,\ell} = 1$ and Compute $p_{s,j,k}^{wind,\ell} = \sum_{s\in\mathcal{S}} w_{s,\ell}\cdot p_{s,j,k}^{wind}$
2) Solve Stochastic Problem with $M$ Batches of Realizations

# Stochastic Optimization and Uncertainty Q

## Illinois Study -Wind Adoption 20%-




## Wind Power Profiles